M-DG Seminar:
Multinomial Processing Tree Modeling

Workflow: Developing an MPT Model

Summer semester 2020

Prof. Dr. Daniel Heck

M-DG: Multinomial Processing Tree Modeling

Part	Date	Topic	Literature
(A) Theory	Self study	A1) Introduction	Erdfelder et al. (2009)
		A2) Basics of MPT modeling	Batchelder & Riefer (1999)
		A3) The software multiTree	Moshagen (2010)
		A4) Hierarchical MPT modeling	Lee (2011) Heck et al. (2018)
(B) Application	15.5.*	B1) Questions & Practice with multiTree	Batchelder & Riefer (1986)
	20.5.*	B2) Workflow: Developing an MPT model	Jung et al. (2019)

* Web-Conference, 12:00 – 15:00, https://webconf.hrz.uni-marburg.de/b/dan-fvk-ha6

Workflow: Developing an MPT model

Overview:

1. Decision-inertia paradigm (with audio explanations)
2. Model development
3. Identifiability
4. Testing construct validity

Decision Inertia

- Decision inertia = people tend to stick to a previous decision regardless of its outcome
- Examples:
  - Brand loyalty
  - Telephone contracts from the 1970s
  - Financial investments
  - ...
- Definition (Jung et al., 2018)
  - "Decision inertia is the decision-makers' tendency to repeat the previous decision regardless of the consequences, even if it is clearly inferior to other options."

Decision-Inertia Paradigm (Alós-Ferrer et al., 2016)

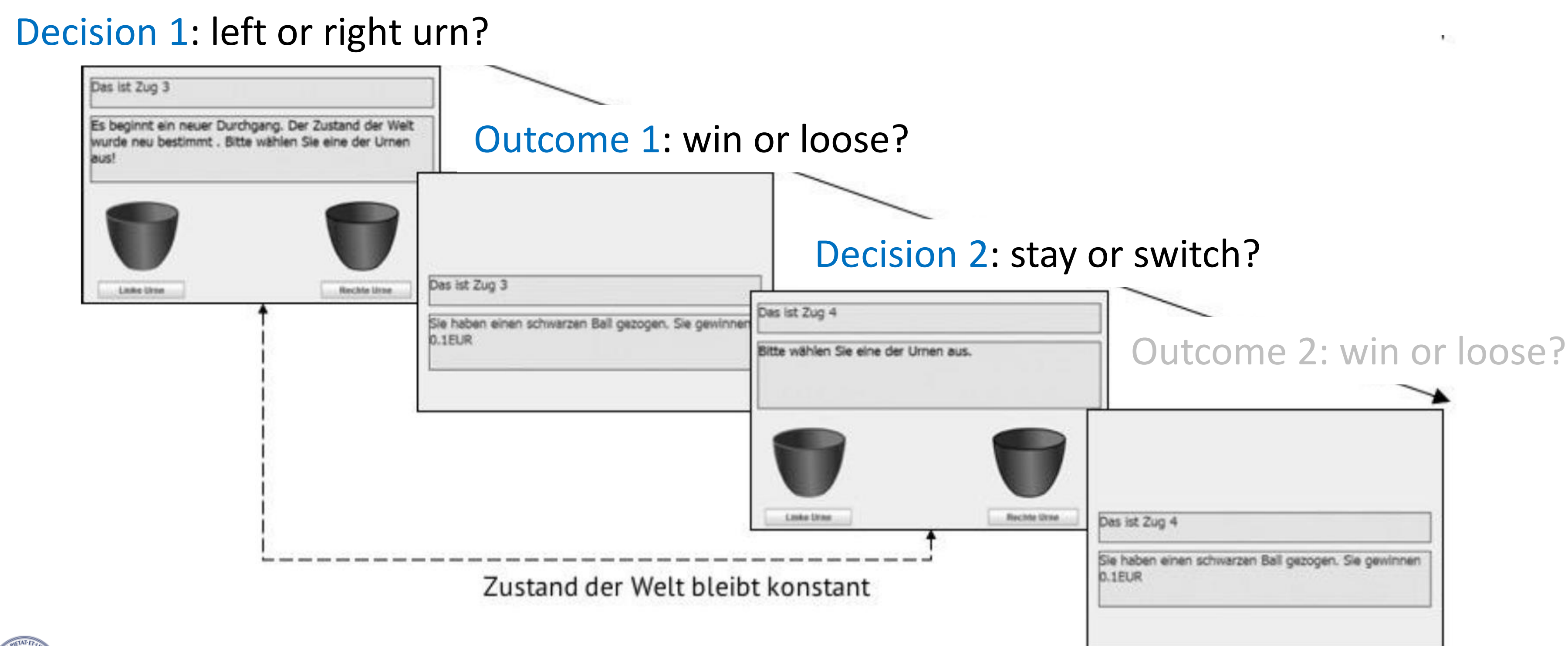
- Participants draw a ball from two urns (Left vs. Right)
- Each urn contains six balls with a different composition of black (= win) and white (= loose) balls

State (Prob)	Left Urn						Right Urn					
Up (1/2)	●	●	○	○	○	○	●	●	●	●	○	○
Down (1/2)	●	●	●	●	○	○	●	●	○	○	○	○

- Participants do not know which urn contains more black balls → unknown state of the world (Up vs. Down)
- Responses: Participants decide two times between Left vs. Right urn

Decision-Inertia Paradigm (Alós-Ferrer et al., 2016)

1. Unknown state of the world is randomly determined
   → Which urn contains more black (= win) balls?
2. Participate makes two decisions:



Standard Analysis

- Rational strategy: Bayesian updating
  - win → stay
  - loose → switch

- Definition of an ad-hoc measure of decision inertia
  - Error rate *K*: Frequency of not following the rational Bayesian strategy (for multiple repetitions of Trial 1 & Trial 2)

- Further analysis: Logistic Regression
  - Criterion: Error rate *K*
  - Predictors: Motivational or cognitive variables

Workflow: Developing an MPT model

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Model Development

- Let’s develop an MPT model of decision inertia together!
- Workflow of developing an MPT model:
  1. Select a *paradigm* (e.g., an experimental task) → Done.
  2. Define the *conditions* of the paradigm
  3. Define *category system* for each condition
  4. List relevant *processes/parameters*
  5. Construct theoretically reasonable *processing branches* („*trees*“) for each condition
  6. Check whether the model is *identifiable*.
  7. Test the *construct validity* of the model.
- General rules for MPT models:
  - As simple as possible!
  - Ignore unlikely events!

Decision Inertia MPT Model

2\. & 3. What are the conditions & response categories?

???

Decision Inertia MPT Model

2. & 3. What are the conditions & response categories?

Conditions:

Optimal choice in Trial 1

Suboptimal choice in Trial 1

Response categories:

stay

switch

stay

switch

Decision Inertia MPT Model

4. What are the relevant latent processes?

???

Decision Inertia MPT Model

4. What are the relevant latent processes?

Model assumptions:

- Choices in Trial 2 are affected by two latent processes:

1. Decision Inertia: active vs. inactive
   → Parameter d
2. Bayesian Updating: active vs. inactive
   → Parameter c_1 (if decision inertia is active)
   → Parameter c_2 (if decision inertia is inactive)

Decision Inertia MPT Model

4. What are the relevant latent processes?

More model assumptions:

- Mapping of latent processes to responses:

1. If none of the two processes is active in Trial 2, people choose randomly
2. If exactly one process is active in Trial 2, this process determines the choice
3. If both processes are active in Trial 2, Bayesian updating dominates over decision inertia

Decision Inertia MPT Model

6. Construct theoretically reasonable processing branches („trees“) for each condition

Conditions:

Optimal choice in Trial 1

Suboptimal choice in Trial 1

???

Response categories:

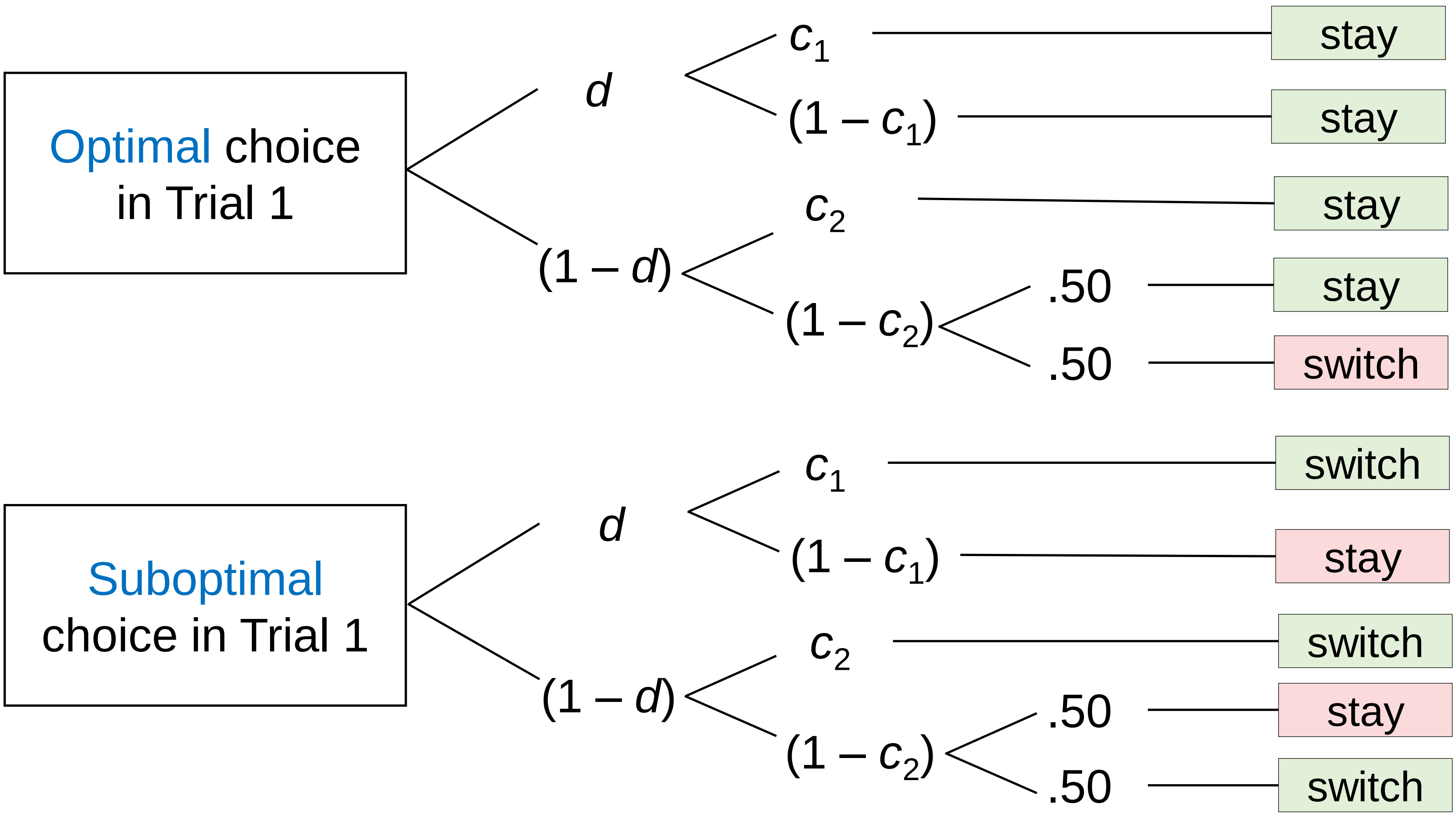
stay

switch

stay

switch

Decision Inertia MPT Model



Parameters:

- d = decision inertia
- c_1 = Bayesian updating (if DI)
- c_2 = Bayesian updating (if no DI)

Workflow: Developing an MPT model

Overview:

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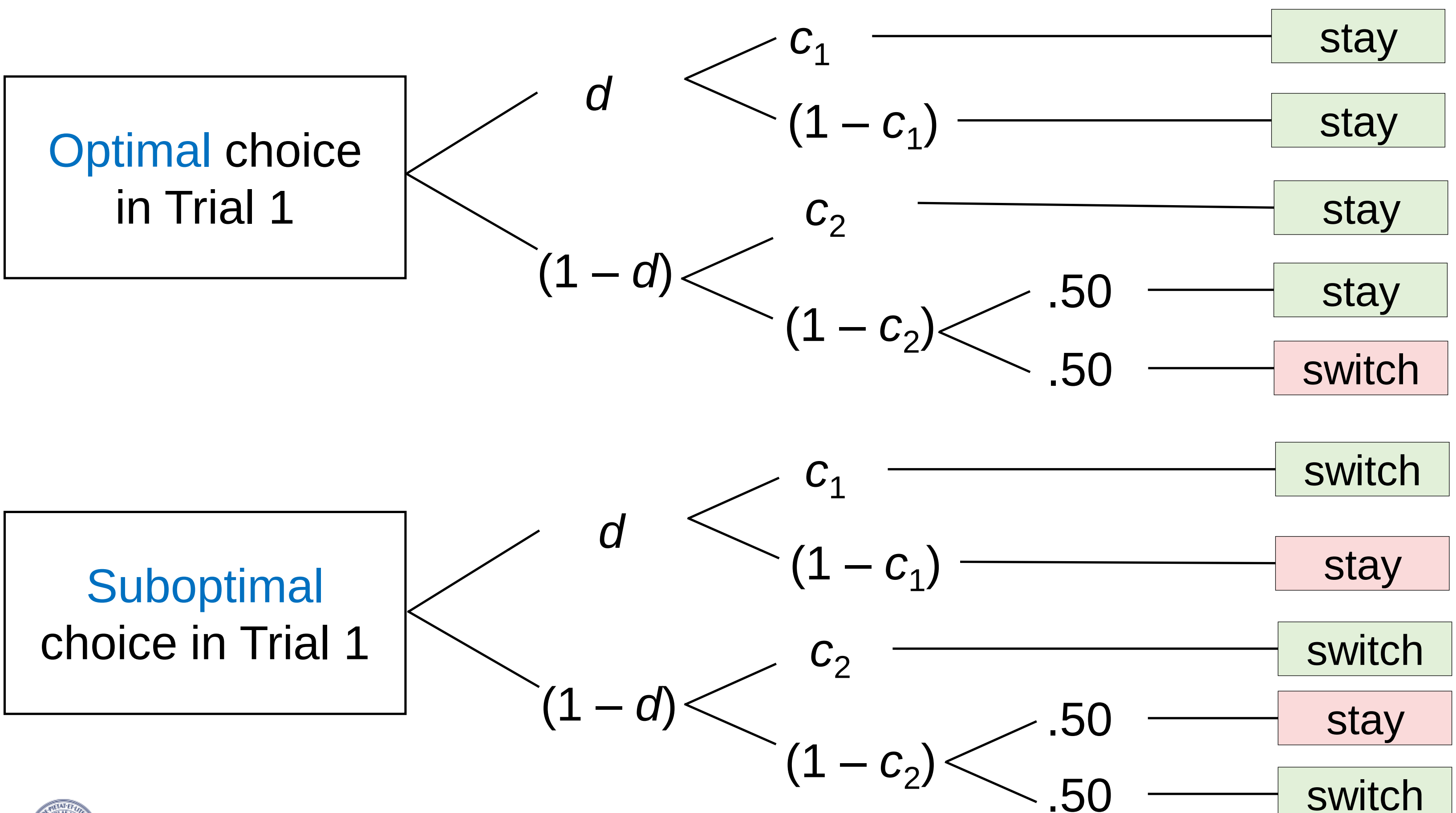
Decision Inertia MPT Model: Identifiability

???

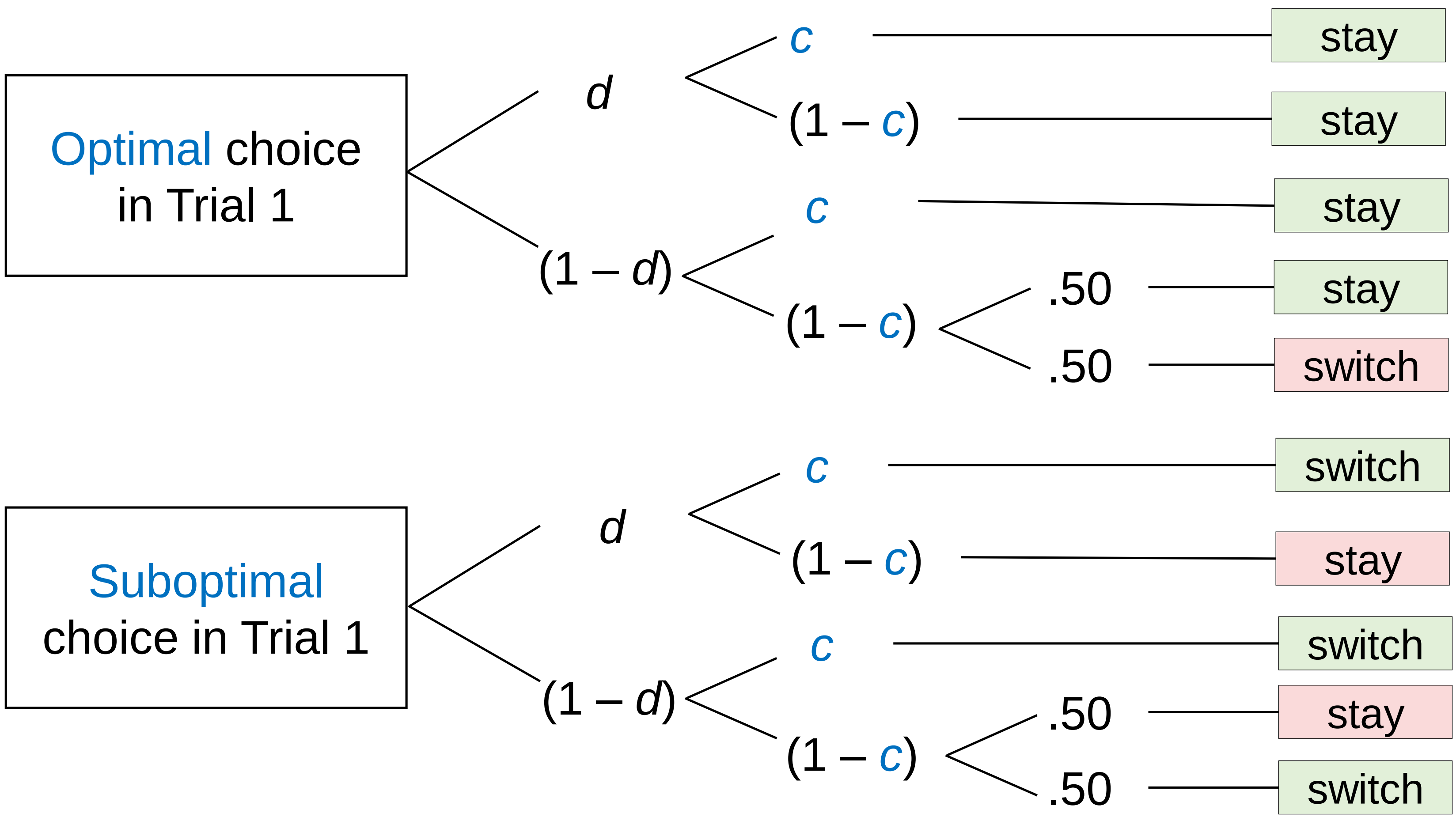
6. Is the baseline model with 3 parameters identifiable?

= Is it possible to get unique parameter estimates?



Decision Inertia MPT Model: Identifiability ???

6. Is the independence model with $c_1 = c_2$ identifiable?



Application to Empirical Data

Pilot data:

	Trial 2	
Trial 1	stay	switch
Optimal choice (win)	895	105
Suboptimal choice (loose)	195	805

Exercises:

1. Fit the independence model with 2 parameters ($c_1 = c_2$)
2. Interpret the parameter estimates.

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Decision Inertia MPT Model: Validity

- Construct validity
  - How can we test whether the parameters measure what they are supposed to measure?
- Selective influence
  - An experimental manipulation should selectively influence a specific parameter but no the others

7. Do you have ideas for experimental manipulations of:
   a) Decision inertia (*d*)
   b) Bayesian updating (*c*)

???

Decision Inertia MPT Model: Empirical Validation

7. Do you have ideas for experimental manipulations of:
   a) Decision inertia (*d*)
   b) Bayesian updating (*c*)

→ Predictions of selective influence:

- Decision inertia increases if one makes the first decision by *themselves* (instead of being provided with a *fixed* decision)
- Bayesian updating increases if rational decisions become *easier* (= if base rates are more extreme)

→ Empirical test in a 2 x 2-factorial design:

- Factor A: First choice fixed vs. free (→ effect on *d* but not on *c*)
- Factor B: 80% vs. 60% success rate (→ effect on *c* but not on *d*)

Decision Inertia MPT Model: Empirical Validation

Results 1: Model comparison

- Model fit of the base model (with $c_1 \neq c_2$):
  - 6 Parameters: $c_1^{60\%}$, $c_1^{80\%}$, $c_2^{60\%}$, $c_2^{80\%}$, d^{fixed}, d^{free}
  - $G^2(2) = 1.87$, $p = .392$
  - ΔBIC = -15.15

- Model fit of the independence model (with $c_1 = c_2$):
  - 4 Parameters: $c^{60\%}$, $c^{80\%}$, d^{fixed}, d^{free}
  - $G^2(4) = 9.41$, $p = .052$
  - $\Delta G^2(2) = 7.54$, $p = .023$
  - ΔBIC = -24.62

Decision Inertia MPT Model: Empirical Validation

Results 2: Parameter estimates

- Note: Estimates are based on the independence model

- Factor A should affect Decision Inertia
  - Choice in Trial 1 fixed: $\hat{d} = .141$ (SE = .042)
  - Choice in Trial 1 free: $\hat{d} = .453$ (SE = .041)

- Factor B should affect Bayesian Updating
  - Success rate 60%: $\hat{c} = .591$ (SE = .016)
  - Success rate 80%: $\hat{c} = .715$ (SE = .014)